Knowledge Synthesis Methods

13. Bayesian Belief Networks[1]

Summary of method

A semi-quantitative modelling approach that combines empirical data with expert knowledge to calculate the probability of a specific outcome or set of outcomes.

Similar to the Causal Criteria Analysis, the method first builds a visual representation of the system. Probabilities for each link can be based on expert judgement, literature review, or a prescribed mechanistic model. The BBN model can then generate a range of probabilities for the final outcome, based on the underlying system.

The main output is a diagrammatic interpretation of a system showing probabilistic relationships and outcomes within a causal chain.

This method explicitly incorporates uncertainty about linkages in a causal chain via conditional probabilities. For example, a BBN could quantify likelihood of storm events large enough to impact coastal ecosystems.

Key references

Cooper, G. F., & Herskovits, E. (1992). *A Bayesian method for the induction of probabilistic networks from data.* Machine learning, 9(4), 309-347.

Landuyt, D., Broekx, S., D'hondt, R., Engelen, G., Aertsens, J., & Goethals, P. L. (2013). *A review of Bayesian belief networks in ecosystem service modelling.* Environmental Modelling & Software, 46, 1-11.

McCann, R. K., Marcot, B. G., & Ellis, R. (2006). *Bayesian belief networks: applications in ecology and natural resource management.* Canadian Journal of Forest Research, 36(12), 3053-3062.

Examples of application

Nyberg *et al.* (2006) present a case study of a BBN used during adaptive management of forest lichens in Canada.

Thorne *et al.* (2015) describe the use of a BBN with stakeholders managing tidal marshes across San Francisco Bay, USA.

[1] A guidance note from Dicks LV, Haddaway N, Hernández-Morcillo M, Mattsson B, Randall N, Failler P, Ferretti J, Livoreil B, Saarikoski H, Santamaria L, Rodela R, Velizarova E, and Wittmer H. (2017). *Knowledge synthesis for environmental decisions: an evaluation of existing methods, and guidance for their selection, use and development – a report from the EKLIPSE project.*

Nyberg, J. B., B. G. Marcot, and R. Sulyma. (2006). *Using Bayesian belief networks in adaptive management.* Canadian Journal of Forest Research 36:3104-3116. NOT OPEN ACCESS.

Thorne, K. , B. J. Mattsson, J. Takekawa, J. Cummings, D. Crouse, G. Block, V. Bloom, M. Gerhart, S. Goldbeck, J. O'Halloran, B. Huning, N, Peterson, C. Sloop, M. Stewart, K. Taylor, and L. Valoppi. (2015). *Collaborative decision-making framework to optimize resilience of tidal marshes in light of climate change uncertainty.* Ecology and Society 20 (1): 30.
[online] URL: http://www.ecologyandsociety.org/vol20/iss1/art30/

Bayesian Belief Networks

Cost	Staff: 1 week – 3 months FTE Depends on • Software used, some freeware and trial versions available • The number of stakeholders/experts involved • Level of disagreement among stakeholders/experts • Number of revision rounds→ depending on further use of the BBN • Level of detail: text or tabular explanation of the BBN, and number of nodes (factors) and relationships (links) in BBN • Facilitator/moderator, if done in participatory mode • Need and availability of existing predictive models to inform BBN structure and probabilities • If Bayesian decision network (BDN), then availability of utility values (value trade-offs in the case of multiple objectives) • Scale of the problem (no of sectors, countries involved/addressed)
Time required	1 week to 3 months If preparatory work is done (causal chain ready for conversion to BBN, elicitation process set up if needed, predictive models ready if relevant and available, facilitators ready if participatory), can be done in 1 day. Several days of preparatory time are likely to be required
Repeatability	Low. If you do it with two different groups of people or individuals, the BBN structure (if done from scratch) and probabilities will likely differ

Transparency	Moderate Allows for mathematical rigor and sensitivity analysis to evaluate robustness of outcomes or recommendations to uncertainty. BUT quantification of the system relationships (and stakeholder values in the case of a BDN) can be challenging for non-technical stakeholders Depends on level of documentation for the reasoning and methods used to develop and parameterize the BBN
Risk of bias	Moderate. Quantification if done properly can avoid biases compared to purely qualitative approaches Depends on: • representativeness of stakeholders/experts • whether individual input is incorporated or obtained in group discussion • quality of any data and predictive models incorporated • quality of underlying causal chain conceptual model
Scale (or level of detail)	Flexible
Capacity for participation	Moderate. Depends on who is engaged. Could be just experts
Data demand	Depends on available predictive models and literature data Can point to further data demands Requires expert judgement Requires quantified stakeholder values (BDN)
Types of knowledge	Scientific, technical, opinion-based; tacit
Types of output	Flow diagram, causal chain Likelihoods (probabilities) of particular outcomes. For example, 80% chance that fish abundance will be <50 if a particular policy option is implemented Quantified expected stakeholder satisfaction associated with alternative management/policy options (BDN) Explanatory report/information attached
Specific expertise required	Requires an analyst with background in quantitative modelling especially statistics and probability, plus familiarity with at least one BBN software For participatory expert/stakeholder-based parameterization, requires skills in creating teams, facilitation, parameterization For parameterization based on existing literature or predictive models, need topic experts familiar with any underlying predictive models and/or literature

Strengths	Weaknesses
Potential for system perspective of a problem: can include multiple scales, multiple sectors, multiple actors Flexible level of complexity: can be done in a very simple manner by one person or in a complex participatory manner Visualization Can be used transparently, if done in a participatory manner and BBN is kept simple enough so that all participants can understand the underlying mathematics Provides probabilities of outcomes Clearly and quantitatively represents uncertainty Can directly provide policy/management recommendations (BDN) Can be used to quantify value of collecting more information / research to inform a recommendation (BDN)	Can be biased, depending on facilitation and representativeness Requires quantitative modelling skills to set up and parameterize BBN Requires topical expert input Requires knowledge-holder input if developed in participatory manner or as a BDN